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Future Position Prediction for Pressure Refuelling Port of Commercial Aircraft

School of Aerospace, Transport and Manufacturing
Computational and Software Techniques in Engineering

MSc
Academic Year: 2023–2024

Supervisors: Dr Boyu Kuang and Dr Stuart Barnes
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This thesis is submitted in partial fulfilment of the requirements for the degree of MSc.

Academic Integrity Declaration

I declare that:

- the thesis submitted has been written by me alone.
- the thesis submitted has not been previously submitted to this university or any other.
- that all content, including primary and/or secondary data, is true to the best of my knowledge.
- that all quotations and references have been duly acknowledged according to the requirements of academic research.

I understand that to knowingly submit work in violation of the above statement will be considered by examiners as academic misconduct.

Abstract

Replace with your abstract text of not more than 300 words.

Keywords:
Replace with at least 6, semicolon seperated keywords (not contained within the thesis title) – this makes the thesis searchable.

Acknowledgements

The author would like to thank . . .

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List of Abbreviations

ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
EKF	Extended Kalman Filter
AAGR	Autonomous Aircraft Ground Refueling
AGR	Aircraft Ground Refueling
UAV	Unmanned Aerial Vehicle
AAR	Autonomous Aerial Refueling
DGPS	Differential Global Positioning System
SVM	Support Vector Machine
HOG	Histogram of Oriented Gradients
SOTA	State-of-the-Art
AIS	Automatic Identification System
GPS	Global Positioning System

Chapter 1

Introduction

Ground pressure refuelling is a standard method used to refuel commercial aircraft safely and efficiently. This process involves using a hydrant system, which consists of underground fuel pipelines connected to a network of fuel hydrants located at aircraft parking positions [6]. The hydrant system is supplied with fuel from storage tanks, typically located near the airport [16].

When an aircraft is ready for refueling, a hydrant dispenser vehicle, also known as a hydrant truck or cart, is connected to the hydrant pit using a flexible hose [22]. The hydrant dispenser vehicle is equipped with a pressure control valve, a flow meter, and a filtration system to ensure that the fuel meets the required quality standards [3].

The refueling process begins by connecting the hydrant dispenser vehicle to the aircraft's fuel panel using another flexible hose [22]. The pressure control valve on the hydrant dispenser vehicle is then used to regulate the fuel pressure and flow rate, ensuring that the fuel is delivered to the aircraft at the appropriate pressure and volume [3].

One of the main advantages of pressure ground refueling is its efficiency. This method allows for high fuel flow rates, which can significantly reduce aircraft turnaround times [6]. Additionally, the use of underground pipelines eliminates the need for fuel trucks, reducing traffic congestion and the risk of accidents on the apron [16].

Safety is another critical aspect of pressure ground refueling. The hydrant system is designed with multiple safety features, such as emergency shutdown valves and leak detection systems, to minimise the risk of fuel spills and fires [3]. Moreover, the hydrant dispenser vehicles are equipped with safety devices, such as dead man switches and bonding cables, to prevent incidents during the refueling process [22].

Figure 1.1: Pressure Refuelling of a Commercial Aircraft. Source: Tom Boon/Simple Flying

The aviation industry is undergoing a significant transformation with the advent of intelligent airports based on highly automated systems. Among these, automated refuelling systems play a crucial role in ensuring efficient and accurate refuelling of aircraft. However, one of the main challenges of this automation process is the accurate detection of the aircraft's refuelling port, which is relatively small and can easily be obscured by other visual elements on or near an aircraft. Scanning the entire area of each video frame is both time-consuming and inaccurate. It is therefore essential to develop a more efficient and accurate method of locating the refuelling port.

This thesis aims to address this challenge by developing a new AI model that uses the temporal relationships between successive frames of a video to predict the location of the refuelling port in subsequent frames. By focusing the analysis on the most relevant areas of the video sequence, this approach has the potential to optimise both the speed and accuracy of the refuelling system.

Specific objectives of this thesis include conducting a comprehensive review of state-of-the-art object detection and tracking methods, designing and developing a real-time computer vision system capable of accurately detecting and tracking the pressurised refuelling port of a commercial aircraft, the implementation and evaluation of deep learning time series models for future position prediction, the integration of Extended Kalman Filtering (EKF) into deep learning models to improve the accuracy and robustness of future position predictions, and the development of a real-time framework for predicting the future position of the pressurised refuelling port.

By achieving these objectives, this thesis aims to make a significant contribution to the development of intelligent airport systems and to improve the efficiency and accuracy of automated refuelling systems at airports, while reducing computing power requirements. The proposed framework has the potential to be applied in various scenarios, such as different lighting conditions, angles and orientations of refuelling ports, making it a versatile and effective solution to the challenges of automated refuelling systems.

Chapter 2

Literature Review

2.1 Automated Refulling Systems in the Aviation Industry

2.1.1 Introduction to Automated Refuelling Systems

Automated refueling systems have gained substantial importance in the aviation industry due to their potential to enhance safety and efficiency. The concept of Autonomous Aircraft Ground Refueling (AAGR) emerged in the 1980s, with initial implementations featuring numbered markers near refueling ports to aid in image processing and robotic automation [23, 4, 17].

These systems streamline the refuelling process by using state-of-the-art mechanisms and technologies to ensure accuracy and speed. A key element is the pressurised fuel adaptor, which connects seamlessly to the aircraft [28]. Methods such as 'PosEst' have been proposed to capture and track objects in 3D, enabling the pressurised refuelling port to be located precisely. [29].

In addition, autonomous in-flight refuelling technologies for Unmanned Aerial Vehicles (UAV-AARs) have also been developed to extend their range, endurance and payload capacity without significantly altering their original design. This technology overcomes limitations in fuel capacity and endurance, enabling UAVs to undertake longer missions [11].

2.1.2 Challenges in Automated Refuelling

The implementation of AAGR presents a number of challenges, including varying lighting conditions, different refuelling port designs and potential obstructions. Confidentiality issues associated with aircraft refuelling data, as well as the lack of standardised workflows, also complicate the deployment of advanced AAGR solutions, based on [17] data.

Accurately detecting and estimating the position of the fuelling adaptor is a major hurdle. Current methods that rely on artificial features often encounter occlusions and suffer from reduced reliability due to a low signal-to-noise ratio, particularly over long distances [29]. Variability in lighting, weather conditions and the physical state of the refuelling adapter further complicates detection and localisation [30]. Vision-based systems must operate in real time and with minimal computational load, adding a new layer of complexity.

The development of high-quality data sets for training and monitoring automated refuelling systems is another major challenge. Collecting and processing these datasets is often time-consuming and requires meticulous configuration [28].

2.1.3 Current Technologies and Methods

Visual measurement methods based on artificial features, such as spray marks or LEDs, are commonly used in today's automated refuelling systems. The VisNav system, developed by Valsek, uses light-emitting diodes emitting at different frequencies to locate the centre of a beacon, employing a Gaussian least squares differential correction algorithm to calculate the position of the [29] refuelling adaptor. Despite the advantages of these methods, they remain sensitive to occlusion and low signal-to-noise ratios at long distances.

Recent advances in Automatic Aircraft Ground Refuelling (AAGR) rely on computer vision, artificial intelligence and robotics to achieve high levels of automation. The integration of these technologies with Big Data has significantly improved the feasibility and accuracy of AAGR systems thanks to the creation of large datasets for training and validation. For example, an Aircraft Ground Refuelling (AGR) dataset comprising more than 3,000 images from 13 databases was expanded to more than 26,000 images after augmentation, enabling AGR scene recognition through image mining, augmentation and classification [17]. In addition, recent innovations have introduced hybrid datasets combining real and synthetic data for training and validating [30] systems. This approach offers a wide range of scenarios and conditions, improving the robustness and accuracy of automated refuelling systems.

Furthermore, in the field of autonomous aerial refuelling, current technologies rely mainly on vision-based systems and sophisticated control algorithms. These methods use a variety of sensors, including monocular and binocular cameras, to detect and track drugs and refuelling probes. Wang et al. [25] demonstrated the feasibility of real-time drug recognition and 3D localisation for autonomous aerial drone refuelling using monocular computer vision. In addition, Chen and Stettner [7] explored the application of 3D flash lidar for drug tracking [25]. The probe and drogue refuelling system involves the refuelling aircraft towing a refuelling hose with a drogue at the end, while the pilot of the receiving aircraft manoeuvres to insert the probe into the drogue. For unmanned aerial refuelling, this process is carried out autonomously. Although DGPS offers high location accuracy, it faces challenges such as lock-in problems and low bandwidth in air-to-air refuelling applications [33].

2.1.4 Future Directions and Innovations

Future progress in AAGR will depend on systematic research and improvements in training processes and classifier design. One promising approach is to use image style transformation technologies based on generative models to simulate changes in real-world visual conditions such as weather, lighting and camera angles [17]. However, these technologies need to be refined to become specific to aircraft ground refuelling scenarios.

Expanding the training datasets to encompass various aircraft models and exploring alternative filtering methods to reduce system delays are also key to future improvements. Ongoing technological developments are expected to minimise human intervention in refuelling tasks, paving the way for more efficient and accurate autonomous systems [29].

Validation of the results using other measurement methods, such as laser trackers, and testing of the systems developed on passenger aircraft under real conditions are essential steps. This research aims to ensure the reliability and applicability of automated refuelling systems in operational environments [30].

Advances in computer vision algorithms and hardware will be key to improving the accuracy and reliability of position measurements. Innovations in sensor fusion, combining data from various sources such as vision systems and Differential Global Positioning Systems (DGPS), could lead to more robust solutions. Improved real-time image processing capabilities and sophisticated filtering techniques, such as the Extended Kalman Filter (EKF), are likely to play a key role in the evolution of autonomous aerial refuelling technologies [33].

Further integration of advanced computer vision techniques and machine learning algorithms can significantly improve the accuracy and reliability of the refuelling process. The development of more sophisticated synthetic datasets that simulate a wider range of conditions and scenarios will improve the system's ability to handle real-world variations and anomalies [28].

By continually refining these systems, the aviation industry is one step closer to achieving fully autonomous and highly efficient refuelling operations, marking an important milestone in intelligent airport operations and advances in aviation safety.

2.2 Object Detection and Tracking in Computer Vision

2.2.1 Fundamentals of Object Detection and Tracking

Object detection and tracking are fundamental tasks in computer vision, involving the identification and continuous observation of objects in a video sequence. Traditional tracking algorithms mainly use visual information to locate the target by building a model that estimates the similarity between the target and the search region. However, these models often fail in complex scenes populated with similar objects, leading to confusion and loss of the target. Innovations such as the KYS algorithm proposed by Bhat et al. [5] incorporate scene information represented as dense localised state vectors, which are propagated throughout the sequence to provide additional context to the appearance model. The LaSOT dataset further enhances tracking by providing linguistic specifications that describe the target and its environment, conveying valuable semantic information that aids tracking in complex scenes [8]. These advances are crucial for applications such as automated refuelling systems, intelligent transport and industrial automation, where accurate object detection and tracking are imperative for efficiency and safety [20, 32].

2.2.2 Algorithms and Techniques for Object Detection

In the field of object detection, a plethora of algorithms and techniques have been developed to improve accuracy and robustness. Performance metrics such as accuracy, robustness, precision, recall and mean accuracy (mAP) are essential [9]. The best-known models for single small object detection include the fast R-CNN, SSD: Single Shot Multibox Detector, and YOLO (You Only Look Once), each evaluated on datasets such as Microsoft COCO and PASCAL VOC [9, 26, 31]. Generative trackers, capable of handling challenging scenarios such as occlusion and large-scale variation through particle sampling strategies, are often integrated with various appearance models, including sparse representation and energy of motion. Discriminative trackers, by contrast, build robust classifiers using hand-crafted or deep features [8]. The combination of generative and discriminative approaches, as well as the integration of deep learning techniques such as fully revolutionary networks and Transformer models, has led to significant improvements in object detection performance [20, 32, 31]. In addition, the speed and computational requirements of these algorithms are critical factors influencing their practical applicability [32, 31, 18].

2.2.3 Advanced Techniques for Object Tracking

Advanced techniques in object tracking leverage both generative and discriminative models to amplify tracking efficacy. The utilisation of deep trackers has evidenced superior results on public tracking datasets, attributed to their potent feature extractors, accurate bounding box regressors, and discriminative classifiers [18]. Techniques such as deformable convolution and Transformer models extend traditional convolution or correlation methodologies to execute global feature matching, thereby enhancing tracking accuracy. The incorporation of contextual or knowledge information can substantially elevate performance, with methodologies like Particle Filtering, also recognised as Sequential Monte Carlo (SMC) methods, framed as problems of Bayesian inference in state space [9, 26]. The extended Kalman Filtering (EKF) is another advanced technique that has been employed to improve tracking accuracy by predicting the current status through the previous status and modifying the prediction result based on observation information [32, 31]. Despite these advancements, the integration of these methods in a complementary manner remains an open research area with substantial potential for advancing the field [20, 32].

2.2.4 Challenges and Future Research Directions

Despite considerable progress, several challenges persist in the domain of object detection and tracking. A primary challenge is the integration of language and visual information to enhance tracking in complex scenes. Semantic information derived from language specifications can furnish valuable context that aids trackers in more accurately locating targets [8]. The Drifting Problem, where inaccuracies in foreground and background estimation degrade the appearance model over time, particularly during occlusions or imprecise object locations, remains a significant issue. Additionally, challenges such as motion blurring, limited camera equipment, and the necessity for real-time processing must be addressed [20]. Future research should emphasise developing comprehensive large-scale datasets tailored for small object detection, like SODA-D and SODA-A, focusing on driving and aerial scenarios respectively [9, 26]. Further, exploring the potential of multi-modal information, enhancing multi-frame processing techniques such as optical flow estimation for key frames, and creating adaptive tracking systems capable of adjusting to appearance variations due to rotations, geometric transformations, and texture changes, are critical areas for future exploration [8, 20, 26, 32, 31, 18].

2.3 Deep Learning for Spacio-Temporal Prediction

2.3.1 Fundamentals of Time Series Prediction

Time series prediction involves processing sequential data to predict future events or values. Various deep learning models have been applied to this task, requiring several preparatory steps such as collecting data, designating attribute types, dealing with inconsistencies and storing datasets. These datasets are usually classified into units of time such as seconds, minutes and hours, allowing the construction of metadata for machine learning [19].

The problem of locating future objects has been widely studied, particularly for static surveillance cameras, from a bird's-eye view. Early work used recurrent neural networks (RNNs), including long-term memory networks (LSTMs) and managed recurrent units (GRUs), in an encoder-decoder format to encode past observations and decode future locations. Additional inputs, such as environmental information and semantic actions, were used to improve prediction accuracy. Alahi et al. [1] proposed a Social-LSTM to model pedestrian trajectories and interactions, further improving global context capture through a social pooling module [15]. Recent advances have taken advantage of generative models and attention mechanisms to handle complex scenes involving various interacting agents [15].

The article of Xu et al. [27] discusses various deep learning models used to predict time series. In particular, the work by Feng et al. [10] uses attentional recurrent networks to predict human mobility [27]. In addition, the paper highlights the use of BERT4Rec, which exploits bidirectional representations of transformer encoders for sequential recommendation tasks [27].

Several models for predicting ship trajectories have been proposed. Anderson considered ship trajectories as a one-dimensional Gaussian process and predicted smoothed trajectories by combining the dynamics with joint prior density and covariance matrices. Jiang et al. [13] used a polynomial Kalman filter for recursive trajectory prediction with minimal memory usage. kai Zhang et al. [14] adopted a spatial clustering method for prediction, using the DBSCAN model to cluster and denoise the original AIS trajectories. Rong introduced a probabilistic model describing the uncertainty of future ship positions through continuous probability distributions, which achieved high prediction accuracy [21].

2.3.2 Recurrent Neural Networks and Long Short-Term Memory Networks

Recurrent neural networks (RNNs), including long-term memory networks (LSTMs) and managed recurrent units (GRUs), have shown promise for predicting the future locations of traffic agents [15]. However, many RNN-based models suffer from performance degradation over time due to their reliance on recurrent prediction of future bounding boxes from previous outputs. The Fusion-GRU model addresses these challenges by exploiting multiple sources of information, such as location scale data, monocular depth information and optical flow data. This approach improves representation learning by capturing the complex interactions between the various information cues, thereby improving the future localisation of traffic agents in congested and risky driving scenes [15].

RNNs are powerful for processing sequence information and making time-based predictions. Hochreiter et al. improved the structure of the RNN unit, introducing the LSTM model to solve the problems of gradient fading, gradient explosion and insufficient information memory through a gating [21] mechanism. LSTMs make efficient use of long-range temporal information, which is useful in a variety of prediction tasks. However, BP neural networks and SVMs also exist for trajectory prediction, but have limitations such as weaker handling of non-linear problems and susceptibility to local extrema [21].

2.3.3 Transformer models for sequence prediction

Recent research has used transform-based methods for estimating the future location of traffic citeFusionGRU agents. Despite advances in deep learning for locating objects in typical driving scenarios, predicting locations in risky scenarios remains challenging due to abrupt changes in motion and interdependencies between successive images [15].

The Transformer model, introduced by Vaswani et al. [24], has revolutionised sequence modelling with its efficient and powerful network structure. For mobility prediction, Transformer models are increasingly recognised for addressing the challenges of predicting individual mobility patterns. The Hong et al. [12] study shows how transformers can effectively learn mobility patterns from historical data, achieving state-of-the-art performance in next-location prediction tasks.

Further validation and extensive experiments on real-world datasets affirm their efficacy in improving prediction accuracy. The work of Xu et al. [27] discusses the application of transformers and self-attention mechanisms in sequence prediction, highlighting their effectiveness in various contexts.

2.3.4 Challenges and Future Research Directions

Despite significant advances, several challenges persist in deep learning models for time series prediction. One of the main challenges is the performance degradation of RNN-based models over time, addressed by models such as Fusion-GRU, which exploit multiple data sources for better representation [15]. Accurate prediction in risky driving scenarios, involving sudden or abrupt changes in motion, is still unresolved. Future research could focus on improving model robustness in these scenarios and integrating additional data sources to improve prediction accuracy [15].

The article of Arora et al. [2] identifies several challenges in location prediction using machine learning, highlighting the need for trajectory data quality and extensive pre-processing. Future research could incorporate semantic information to improve prediction accuracy, taking advantage of ensemble techniques and overcoming data limitations. The ensemble architecture recommended in the paper shows a significant reduction in mean distance error compared to reference models [2].

References

1. A. Alahi, K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese. Social lstm: Human trajectory prediction in crowded spaces. volume 2016-December, 2016. doi: 10.1109/CVPR.2016.110.

2. M. Arora, S. Agrawal, and R. Patel. Machine learning technique for predicting location. *International Journal of Electrical and Electronics Research*, 11, 2023. ISSN 2347470X. doi: 10.37391/ijeer.110254.

3. I. A. T. Association. Guidance material on microbiological contamination in aircraft fuel tanks. 2019.

4. R. A. Bennett, Y. C. Shiu, and M. B. Leahy. A robust light invariant vision system for aircraft refueling. volume 1, 1991. doi: 10.1109/robot.1991.131568.

5. G. Bhat, M. Danelljan, L. V. Gool, and R. Timofte. Know your surroundings: Exploiting scene information for object tracking. volume 12368 LNCS, 2020. doi: 10.1007/978-3-030-58592-1_13.

6. S. Blakey, L. Rye, and C. W. Wilson. Aviation gas turbine alternative fuels: a review. *Proceedings of the Combustion Institute*, 33(2):2863–2885, 2011. doi: 10.1016/j.proci.2010.09.011.

7. C.-I. Chen and R. Stettner. Drogue tracking using 3d flash lidar for autonomous aerial refueling. volume 8037, 2011. doi: 10.1117/12.886572.

8. F. Chen, X. Wang, Y. Zhao, S. Lv, and X. Niu. Visual object tracking: A survey. *Computer Vision and Image Understanding*, 222, 9 2022. ISSN 1090235X. doi: 10.1016/j.cviu.2022.103508.

9. G. Cheng, X. Yuan, X. Yao, K. Yan, Q. Zeng, X. Xie, and J. Han. Towards large-scale small object detection: Survey and benchmarks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45, 2023. ISSN 19393539. doi: 10.1109/TPAMI.2023.3290594.

10. J. Feng, Y. Li, C. Zhang, F. Sun, F. Meng, A. Guo, and D. Jin. Deepmove: Predicting human mobility with attentional recurrent networks. 2018. doi: 10.1145/3178876.3186058.

11. K. Gong, B. Liu, X. Xu, Y. Xu, Y. He, Z. Zhang, and J. Rasol. Research of an unmanned aerial vehicle autonomous aerial refueling docking method based on binocular vision. *Drones*, 7, 2023. ISSN 2504446X. doi: 10.3390/drones7070433.

12. Y. Hong, H. Martin, and M. Raubal. How do you go where?: improving next location prediction by learning travel mode information using transformers. 2022. doi: 10.1145/3557915.3560996.

13. B. Jiang, J. Guan, W. Zhou, and X. Chen. Vessel trajectory prediction algorithm based on polynomial fitting kalman filtering. *Journal of Signal Processing*, 5:741–746, 08 2019. doi: 10.16798/j.issn.1003-0530.2019.05.002.

14. S. kai Zhang, G. you Shi, Z. jiang Liu, Z. wei Zhao, and Z. lin Wu. Data-driven based automatic maritime routing from massive ais trajectories in the face of disparity. *Ocean Engineering*, 155, 2018. ISSN 00298018. doi: 10.1016/j.oceaneng.2018.02.060.

15. M. M. Karim, R. Qin, and Y. Wang. Fusion-gru: A deep learning model for future bounding box prediction of traffic agents in risky driving videos. *Transportation Research Record*, 2024. ISSN 21694052. doi: 10.1177/03611981241230540.

16. A. Kazda and R. E. Caves. *Airport design and operation*. Emerald Group Publishing Limited, 3rd ed. edition, 2015.

17. B. Kuang, S. Barnes, G. Tang, and K. Jenkins. A dataset for autonomous aircraft refueling on the ground (agr). 2023. doi: 10.1109/ICAC57885.2023.10275212.

18. J. Kugarajeevan, T. Kokul, A. Ramanan, and S. Fernando. Transformers in single object tracking: An experimental survey. *IEEE Access*, 11, 2023. ISSN 21693536. doi: 10.1109/ACCESS.2023.3298440.

19. W. C. Lee, Y. B. Jeon, S. S. Han, and C. S. Jeong. Position prediction in space system for vehicles using artificial intelligence. *Symmetry*, 14, 2022. ISSN 20738994. doi: 10.3390/sym14061151.

20. S. Liu, D. Liu, G. Srivastava, D. Połap, and M. Woźniak. Overview and methods of correlation filter algorithms in object tracking. *Complex and Intelligent Systems*, 7, 2021. ISSN 21986053. doi: 10.1007/s40747-020-00161-4.

21. L. Qian, Y. Zheng, L. Li, Y. Ma, C. Zhou, and D. Zhang. A new method of inland water ship trajectory prediction based on long short-term memory network optimized by genetic algorithm. *Applied Sciences (Switzerland)*, 12, 2022. ISSN 20763417. doi: 10.3390/app12084073.

22. R. Sati, S. Singh, and R. Yadav. Aircraft fuel system: design, components, and safety. *International Journal of Aerospace Engineering*, 2019:1–12, 2019. doi: 10.1155/2019/6943787.

23. E. R. Schultz. Robotic systems for aircraft servicing/maintenance. *IEEE Aerospace and Electronic Systems Magazine*, 1, 1986. ISSN 08858985. doi: 10.1109/MAES.1986.5005018.

24. A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Łukasz Kaiser, and I. Polosukhin. Attention is all you need. volume 2017-December, 2017.

25. X. Wang, X. Dong, X. Kong, J. Li, and B. Zhang. Drogue detection for autonomous aerial refueling based on convolutional neural networks. *Chinese Journal of Aeronautics*, 30, 2017. ISSN 10009361. doi: 10.1016/j.cja.2016.12.022.

26. J. Wu and S. Xu. From point to region: Accurate and efficient hierarchical small object detection in low-resolution remote sensing images. *Remote Sensing*, 13, 2021. ISSN 20724292. doi: 10.3390/rs13132620.

27. S. Xu, Q. Huang, and Z. Zou. Spatio-temporal transformer recommender: Next location recommendation with attention mechanism by mining the spatio-temporal relationship between visited locations. *ISPRS International Journal of Geo-Information*, 12, 2023. ISSN 22209964. doi: 10.3390/ijgi12020079.

28. S. Yildirim and Z. A. Rana. Reducing the reality gap using hybrid data for real-time autonomous operations. *Mathematics*, 11, 2023. ISSN 22277390. doi: 10.3390/math11071696.

29. S. Yildirim, Z. Rana, and G. Tang. Autonomous ground refuelling approach for civil aircrafts using computer vision and robotics. volume 2021-October, 2021. doi: 10.1109/DASC52595.2021.9594312.

30. S. Yildirim, Z. A. Rana, and G. Tang. Development of vision guided real-time trajectory planning system for autonomous ground refuelling operations using hybrid dataset. 2023. doi: 10.2514/6.2023-1148.

31. S. S. A. Zaidi, M. S. Ansari, A. Aslam, N. Kanwal, M. Asghar, and B. Lee. A survey of modern deep learning based object detection models, 2022. ISSN 10512004.

32. Y. Zhang, T. Wang, K. Liu, B. Zhang, and L. Chen. Recent advances of single-object tracking methods: A brief survey. *Neurocomputing*, 455, 2021. ISSN 18728286. doi: 10.1016/j.neucom.2021.05.011.

33. Z. Zhong, D. Li, H. Wang, and Z. Su. Drogue position and tracking with machine vision for autonomous air refueling based on ekf. volume 2, 2017. doi: 10.1109/IHMSC.2017.151.

Appendix A

Ethical Approval Letter

Insert your Ethical Approval Letter as the first appendix.

Appendix B

Extra Data

This is a sample of thesis text. This is a sample of thesis text. This is a sample of thesis text. This is a sample of thesis text. This is a sample of thesis text.

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